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Wetter-Yet-More-Vulnerable? Drought, Vegetation Dynamics, and Pastoral Coping in Northern Kenya

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How To Cite: Owuoth, J.L.; Onguru, P.; Kweyu, R. Wetter-Yet-More-Vulnerable? Drought, Vegetation Dynamics, and Pastoral Coping in Northern Kenya. *Global South & Sustainable Development* **2026**, *1*(1), 31. https://doi.org/10.53941/gssd.2026.100031

Received: 21 July 2026
Revised: 15 October 2026
Accepted: 12 November 2026
Published: 19 November 2026

Abstract: In the pastoral drylands of East Africa, lived experiences of drought may diverge from long-term instrumental climate trends. This study examined relationships among meteorological drought, vegetation productivity, and pastoral household coping strategies in Kirisia Watershed, northern Kenya. A multi-method approach combined 32 years (1992–2023) of satellite-derived vegetation and climate data with a 2024 household survey of 70 purposively selected pastoral households. Vegetation productivity was assessed using the Normalized Difference Vegetation Index (NDVI), while meteorological drought was characterised using the three-month Standardized Precipitation Evapotranspiration Index (SPEI-3). Time-series decomposition identified four high-confidence vegetation trend changepoints between 1994 and 2020. Trend analysis revealed a statistically significant increase in SPEI-3 over the study period (Mann-Kendall $\tau = 0.221$, $p < 0.001$), while NDVI showed a moderate positive relationship with SPEI-3 at a one-month lag ($R^2 = 0.345$, $p < 0.001$). Household coping was dominated by relief assistance and livestock migration, while education, and respondent age were associated with selected coping strategies. Households also reported longer and less predictable drought conditions despite the positive long-term SPEI-3 trend. We interpret this divergence as; a wetter long-term moisture signal does not necessarily imply lower vulnerability when ecological sensitivity and household coping capacity remain constrained. The findings support integrated watershed-scale drought monitoring that combines climatic indicators with ecological and socioeconomic information.

Keywords: BEAST; coping strategies; meteorological drought; NDVI; pastoral livelihoods; SPEI

1. Introduction

In the pastoral drylands of East Africa, the lived experience of drought and its instrumental record may diverge in ways that challenge the prevailing assumptions of drought research. Household surveys in northern Kenya consistently report worsening drought conditions, declining forage availability, and eroding coping capacity [1–3], while multi-decadal satellite records of moisture availability, show statistically significant trends towards increasing wetness [4]. Drought vulnerability in pastoral systems may not be solely a function of dry conditions, but an interaction between climatic variability, ecological sensitivity, and socioeconomic conditions [5,6]. In sub-Saharan Africa (SSA) however, these interactions remain understudied at the local watershed levels.

Drought is a near-ubiquitous natural hazard, characterized by prolonged below-average precipitation over an area, which has affected over two billion people since the start of the twentieth century [7]. Drought is generally classified into four main types, distinguished by how hydrometeorological deficits originate, propagate, and ultimately affect the economy and daily life. Meteorological drought arises first, when an area experiences below-average precipitation over a sustained period [8]. If this deficit persists, it can develop into agricultural drought, as

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reduced rainfall lowers soil moisture to levels that compromise crop growth during the growing season [9]. Prolonged precipitation shortfalls can, in turn, lead to hydrological drought, as sustained deficits reduce water levels in rivers, lakes, and groundwater reservoirs [10]. Socio-economic drought occurs when the impact of drought moderates economic goods such as food, water, and Hydro-electric power [11].

Meteorological drought is of especial interest in research as it occupies a position of causal primacy in the broader drought cascade [8]. Unlike agricultural and hydrological drought, which may be confounded by human factors such as irrigation and land-use change, meteorological drought isolates a comparatively pure climatic signal [12]. As the initiator of drought, meteorological drought has the longest lead time for early warning, since precipitation deficits emerge months before crop failure or reservoir decline become apparent. In addition, standardized drought indices apply consistent statistical thresholds across regions, making meteorological drought the most readily comparable basis for cross-site and cross-study evaluation [13].

Meteorological drought however remains underrepresented in African empirical literature. Adisa et al [14] in a systematic review found that nearly 75% of drought research on the continent focused on agricultural drought. The negative impacts of this dearth are particularly felt at the sub-national scale, where local climatological expressions often diverge markedly from national averages [4]. In Kenya, where Arid and Semi-arid Lands (ASALs) cover nearly 80% of the landmass, drought frequency has escalated from approximately once per decade in the 1970s to every five years since the 1990s [2]. However, a lack of local-scale meteorological drought characterisation in the country has direct consequences for pastoral resilience planning.

Vegetation productivity may be estimated through satellite-derived indices such as the Normalised Difference Vegetation Index (NDVI) [1,15,16]. Satellite-derived NDVI is widely applied as a proxy for vegetation productivity in data-scarce ASAL settings [15]. The index relies on the contrasting spectral response of plant canopies: healthy vegetation absorbs red light strongly while reflecting near-infrared light, whereas moisture- or stress-affected vegetation shows reduced near-infrared reflectance [17]. This spectral signal correlates positively with aboveground biomass and forage availability in ASAL rangelands [17].

In ASAL pastoral systems, vegetation productivity is both the primary indicator of ecosystem health, and the foundational natural capital upon which livelihoods depend [18]. In these water-scarce ecosystems, vegetation dynamics are highly responsive to rainfall, and therefore remote sensing becomes a highly reliable tool for watershed management. Satellite-derived indices are of particular value in ASAL contexts such as Kirisia Watershed, where ground-based meteorological and vegetation-monitoring networks are sparse. A key limitation is that NDVI is strongly seasonal, so without decomposing the trend from phenological and seasonal cycles, genuine long-term structural change can be obscured [19].

The NDVI and the Standardized Precipitation Evapotranspiration Index (SPEI) co-vary positively in water-limited ecosystems, with drought suppressing vegetation greenness and wetness driving recovery [20–23]. The strength of this relationship is strongly moderated by vegetation type. Drought-resistant woodland and bushland systems buffer against short-term rainfall deficits through deep root systems and physiological drought-tolerance mechanisms, producing moderate SPEI-NDVI correlations [24]. Cloud-based geospatial platforms such as Google Earth Engine now allow consistent, watershed-scale time series of NDVI and SPEI to be derived over multi-decadal periods at low cost, supporting drought management applications that would otherwise be constrained by limited ground infrastructure [25].

The translation of ecological drought stress into household vulnerability is often not determined by vegetation productivity alone. The degree to which a pastoral household can absorb and recover from a drought shock depends on the coping strategies available to it [26,27]. Opiyo et al. [28] demonstrated that coping strategy selection among Turkana pastoralists in northern Kenya was shaped by household size and socioeconomic status. Wafula et al. [29] showed that education level and age were associated with livelihood diversification in Kenyan ASAL households. Musumba et al. [30] found that education, credit access, and household composition predicted livelihood diversification across eight countries in SSA. These studies have however not been consistently linked to local-scale assessments of the ecological conditions within which coping decisions are made.

We conceptualised vulnerability as a product of exposure, sensitivity, and adaptive capacity, not hazard magnitude alone [31]. Three variables map onto these dimensions: SPEI-3 for climatic exposure, NDVI for biophysical sensitivity, and household coping strategies, sociodemographic traits, and social capital for adaptive capacity. These served as indicators of vulnerability. The framing follows that a long-term wetting signal need not translate into lower household vulnerability if sensitivity and adaptive-capacity constraints limit how that moisture converts into livelihood security. We therefore examined exposure, sensitivity, and adaptive capacity together, rather than using the meteorological drought trend alone as a proxy for vulnerability.

This study is a multi-method analysis of meteorological drought, vegetation productivity, and pastoral household coping strategies in Kirisia Watershed, Samburu County, northern Kenya. The ASAL watershed serves as

the primary dry-season grazing reserve for an estimated 80% of the pastoralist population in Samburu County [32], yet has not, to the authors' knowledge, been the subject of a long-term quantitative analysis integrating drought, vegetation productivity, and household coping. The study addressed the following research questions: (i) What are the temporal patterns of meteorological drought and vegetation productivity in Kirisia Watershed, Samburu County, between 1992 and 2023? (ii) What coping strategies are employed by pastoral households in response to meteorological drought in Kirisia Watershed? And (iii) how are these shaped by ecological conditions and household socioeconomic characteristics?

2. Study Area

Kirisia Watershed (Figure 1) is located in northern Kenya within Samburu County. The watershed lies within the semi-arid Ewaso Nyiro North catchment and is an important dry-season grazing area for pastoral communities. The coordinates, area estimates, and gazettement history reported in the previous version require verification against the primary Kirisia source before resubmission and are therefore not reproduced here until that verification is completed.

The climate is semi-arid, with annual rainfall ranging from 600–750 mm and temperatures between 24 °C and 33 °C [32]. Rainfall follows a bimodal pattern: the long rains occur from March to May and the short rains from October to November. The watershed is characterized by high inter-annual variability. In the period Samburu County has experienced seven severe drought events between 2000 and 2023, five of which occurred after 2011 [33]. Vegetation is dominated by drought-resistant woodland species including *Juniperus procera*, *Podocarpus falcatus*, and *Olea europaea* subsp. caudata.

The watershed supports a predominantly Samburu nomadic pastoralist population, with livelihoods centred on cattle, goats, sheep, and camels. Kirisia Forest serves as the principal dry-season grazing refuge for an estimated 80% of the pastoralist population in Samburu County [32]. Vegetation productivity in the watershed is a direct determinant of household food security and livestock asset retention [34,35]. Lands outside the gazetted forest boundary are managed under 13 group ranches which are communally governed under foraging rights [36].

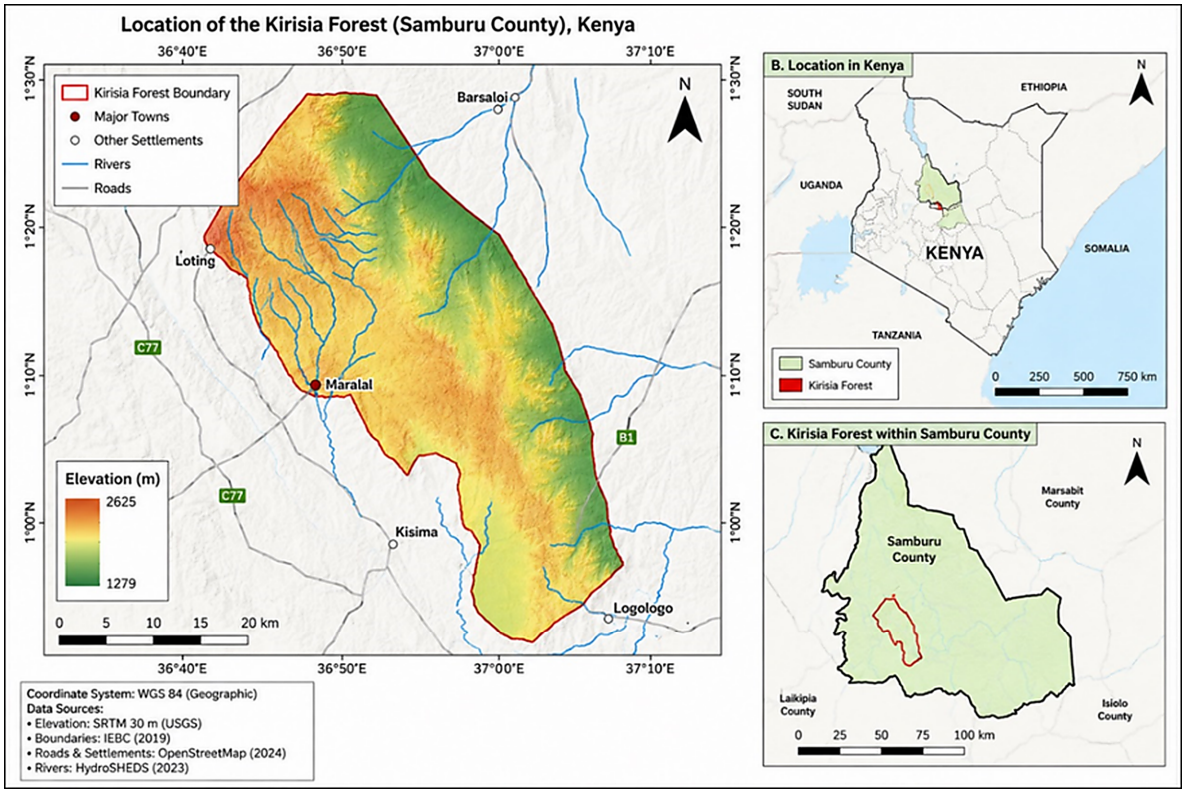

Figure 1. Location of Kirisia Watershed and surveyed households, Samburu County, Kenya.

3. Data and Methods

3.1. Study Design

The study adopted a multi-method quantitative design integrating longitudinal remote sensing analysis with a cross-sectional household survey. Open-ended survey responses on drought perception were analysed using thematic frequency coding to provide supplementary qualitative context.

3.2. Satellite Data and Pre-Processing

Vegetation productivity was assessed using the NOAA AVHRR Normalized Difference Vegetation Index (NDVI) Climate Data Record Version 5 at approximately 5.6 km resolution for 1992–2023 (https://www.ncei.noaa.gov/access/metadata/landing-page/bin/iso?id=gov.noaa.ncdc:C01558 (accessed 13 June 2025)). Daily NDVI was accessed in Google Earth Engine (NOAA/CDR/AVHRR/NDVI/V5), filtered to the study period, and the NDVI band selected. Raw values, stored as scaled integers (in thousands), were rescaled to the standard NDVI range of −1 to 1, and observations were retained only after applying the dataset's quality-assurance filters. Daily NDVI was then averaged over the Kirisia Watershed boundary using a mean reducer and exported. In Python, daily values were averaged to monthly means of all valid observations, giving 384 monthly values from January 1992 to December 2023. Months with no valid observations were left blank and handled by the BEAST model's treatment of missing data (Section 3.3).

Rainfall data were obtained from CHIRPS Version 3.0 (approximately 5 km; Climate Hazards Center, https://data.chc.ucsb.edu/products/CHIRPS/v3.0/daily/ (accessed 6 May 2024)), while temperature data were sourced from the CRU TS4.08 dataset (0.5° resolution; CEDA Archive, https://catalogue.ceda.ac.uk/uuid/715abce1604a42f396f81db83aeb2a4b/ (accessed 2 January 2025)). Both datasets were downloaded directly from their respective archives and clipped to the watershed boundary in Python. Daily CHIRPS grids were summed to monthly totals, and monthly rainfall and temperature were averaged across the watershed. Because CRU grid cells (~55 km) are larger than the watershed, the temperature series represents regional rather than local conditions. The three series were aligned on a common monthly time axis for subsequent analyses.

3.3. Time-Series Decomposition

Vegetation productivity trends were analysed using the Bayesian Estimator of Abrupt Change, Seasonality, and Trend (BEAST) model [37]. This model decomposes time series into trend, seasonal, and change components while estimating uncertainty through posterior probabilities. Changepoints with posterior probability >0.8 were interpreted as high-confidence structural changes.

3.4. Meteorological Drought Characterisation

Meteorological drought was characterised using the three-month Standardized Precipitation Evapotranspiration Index (SPEI-3). Potential evapotranspiration was estimated using the Thornthwaite method. Long-term SPEI-3 trends were assessed using the Modified Mann-Kendall test and Sen's slope estimator. The three-month accumulation period was adopted because it approximates the timescale of rangeland vegetation response to moisture deficits, and is widely used in meteorological drought studies [38]. We acknowledge, however, that drought characteristics are scale-dependent: shorter accumulation periods (e.g., SPEI-1) capture rapid-onset, short-duration deficits more relevant to immediate forage availability, while longer periods (e.g., SPEI-6, SPEI-12) capture cumulative, multi-season moisture deficits more relevant to groundwater recharge and long-term ecosystem stress [39].

SPEI-3 was calculated for the watershed-averaged series and was not mapped spatially. Temperature was taken from CRU TS (0.5°, approximately 55 km), whose grid cells are larger than the watershed; therefore, potential evapotranspiration and the resulting SPEI-3 do not provide meaningful sub-watershed spatial variation. In the absence of ground-based climate stations within the watershed to verify finer-scale patterns, a pixel-level SPEI-3 map would reflect the resolution of the input data rather than actual spatial heterogeneity in moisture conditions. Spatial analysis was therefore limited to NDVI.

3.5. Meteorological Drought and Vegetation Productivity Relationship

The relationship between SPEI-3 and NDVI was examined using Pearson correlation analysis. Lag correlations between one and six months were tested to account for delayed vegetation response to drought, with the strongest lag selected for final analysis. Because the analysis used a watershed-averaged NDVI series, the resulting relationship represents temporal covariation at the watershed scale and should not be interpreted as a pixel-level or household-level causal relationship.

3.6. Household Survey

Household coping data were collected in 2024 through structured face-to-face questionnaires administered to 70 pastoral households across Kirisia Watershed. A pilot study involving 10 households was conducted prior to fieldwork. Associations between sociodemographic variables (marital status, respondent age group, education level) and the adoption of each coping strategy (reported by the household or not; multiple strategies per household

were allowed) were tested using Pearson's chi-square statistic, with *p*-values obtained by Monte Carlo permutation (20,000 replicates) because expected cell counts were below 5 in several cells. No adjustment was made for multiple comparisons, so associations are reported as exploratory. A household was eligible if it derived more than 50% of its income from livestock production [40], as verified by querying the household head on income sources; was located within the Kirisia Watershed boundary; and had a household head or designated adult representative aged 18 years or older able to provide informed consent. Agro-pastoral households combining livestock keeping with crop farming, other non-pastoral households, and households unable or unwilling to provide consent were excluded.

Eligible households were identified with the assistance of two community leaders and two local guides familiar with settlement patterns and pastoral livelihoods across the watershed, in the absence of a comprehensive household census or formal sampling register for the pastoral population of Kirisia Watershed. These informants directed the research team to households located in different parts of the watershed that met the inclusion criteria

Purposive sampling was adopted because no complete sampling frame of pastoral households existed for the watershed at the time of the study, and because the study sought context-specific accounts from households with direct, demonstrated experience of drought impacts and coping rather than statistical representativeness of the wider population. Further, the mobility of Samburu pastoral households during herding activities further necessitated flexible field scheduling, repeat visits, and reliance on community leaders and guides for household access and identification.

3.7. Spatial Trend Analysis

To examine spatial variation in vegetation change, monthly NDVI rasters for 1992–2023 were prepared on the native grid (0.05°, approximately 5.6 km) and clipped to the Kirisia Watershed boundary, retaining every pixel intersecting the boundary. Annual mean NDVI was calculated for each pixel from its monthly values, requiring at least nine valid months per year. For each pixel, the trend in annual mean NDVI was estimated using the Theil–Sen slope [41] and tested with the two-sided Mann–Kendall test [42,43]. Slopes are expressed as NDVI change per decade. To account for testing many pixels, *p*-values were adjusted using the Benjamini–Hochberg false-discovery-rate procedure, and trends were treated as significant at adjusted $p < 0.05$. Pixels were classified as significant increase, significant decrease, or no significant trend. Analyses were conducted in R using the terra and trend packages. The watershed boundary was used as the masking feature; however, all statistics used the full pixel values.

4. Results

4.1. Temporal Changes in Vegetation Productivity

Figure 2 presents the BEAST decomposition of the 31-year NDVI time series for Kirisia Watershed. The seasonal component demonstrates strong, consistent annual periodicity corresponding to the bimodal rainfall pattern of the watershed. The decomposition identifies structural changes in the trend component, while the seasonal component remains comparatively stable. This indicates that the principal long-term changes in NDVI are associated with shifts in the trend rather than a major reorganisation of seasonal periodicity. The high-confidence trend changepoints are described in the following paragraph.

The trend component revealed four changepoints with posterior probabilities exceeding 0.8, representing high model confidence of structural change. These occurred during: (i) 1994–1996, a positive trend shift following the severe 1992–1993 drought, consistent with vegetation recovery as mid-1990s rainfall returned to above-average levels; (ii) 1999–2000, a downward shift coinciding with the most prolonged drought event recorded in this study (6.1 months, minimum SPEI-3 = −1.931); (iii) 2009–2011, a sharp decline and partial recovery, coinciding with the 2011 drought; and (iv) 2018–2020, a decline associated with compounding climatic and anthropogenic stress [36]. The pattern of the most recent two changepoints is particularly telling: each involves a decline phase with incomplete recovery. This trajectory is consistent with declining ecosystem resilience.

Pixel-wise analysis of annual mean NDVI (1992–2023) showed spatially heterogeneous trends across the watershed (Figure 3). Of the 24 pixels intersecting the watershed boundary, 10 showed a significant decline, 3 a significant increase and 11 no significant trend ($p < 0.05$, FDR-adjusted). Significant declines were concentrated in the central and eastern parts of the watershed, with slopes reaching about −0.07 NDVI per decade, whereas significant increases occurred in the north-western interior, the western margin and one southern pixel. Northern pixels showed slopes close to zero. The map describes the spatial pattern of NDVI change only; the drivers of these differences were not tested. Because pixels are about 5.6 km wide and neighbouring pixels are not independent, the pattern should be interpreted as indicative.

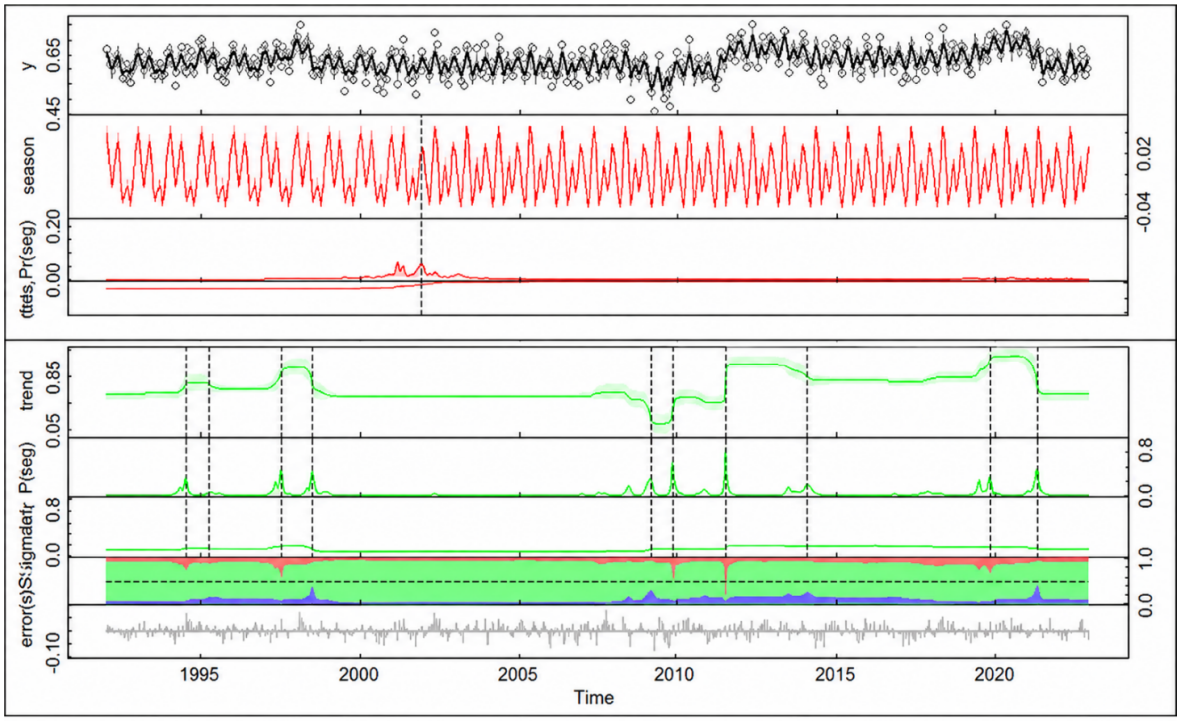

Figure 2. BEAST decomposition output for Kirisia Watershed NDVI, 1992–2023. **Top panel**: original NDVI time series, **second panel**: seasonal component, **third panel**: trend component, and **bottom panel**: posterior probability of trend changepoints.

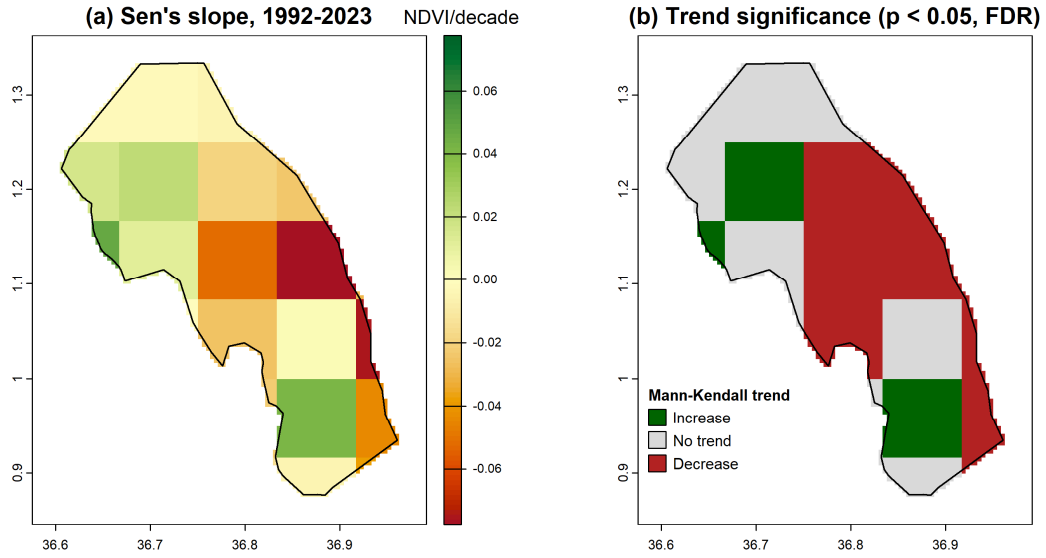

Figure 3. Pixel-wise NDVI trends in Kirisia Watershed, 1992–2023. (**a**) Theil–Sen slope of annual mean NDVI (NDVI per decade). (**b**) Significance of the Mann–Kendall trend test (two-sided, $p < 0.05$, Benjamini–Hochberg FDR-adjusted).

4.2. Meteorological Drought Patterns

Table 1 presents the 12 discrete drought events identified over the study period. Events range from one-month moderate episodes to the prolonged 6.1-month severe event of 2000. Post-2011 events are predominantly moderate and shorter, consistent with the increasing moisture trend.

Figure 4 presents the full SPEI-3 time series for Kirisia Watershed from 1992 to 2023.

The recent period (2016–2023) shows a general shift toward positive SPEI-3 values, with brief dips in 2018–2019 and 2021. A Modified Mann-Kendall test indicates a statistically significant increasing trend in SPEI-3 over the study period ($\tau = 0.221$, $Z = 6.474$, $p < 0.001$), with Sen's slope estimating an annual increase of 0.034 SPEI units per year. This shows a long-term trend towards increasing moisture availability.

Table 1. Meteorological drought events identified in Kirisia Watershed, 1992–2023 (SPEI-3 < −1).

Start Date	End Date	Duration (Months)	Min. SPEI-3	Severity
Mar 1992	May 1992	2.0	−1.746	Severe
Dec 1996	Apr 1997	4.0	−2.206	Extreme
Dec 1998	Mar 1999	3.0	−1.979	Severe
Jun 1999	Aug 1999	2.0	−1.633	Severe
Feb 2000	Aug 2000	6.1	−1.931	Severe
Aug 2002	Sep 2002	1.0	−1.368	Moderate
Apr 2005	Jul 2005	3.0	−1.374	Moderate
Nov 2007	Feb 2008	3.1	−1.836	Severe
Jun 2011	Aug 2011	2.0	−1.392	Moderate
Apr 2014	Jul 2014	3.0	−1.499	Moderate
Sep 2016	Oct 2016	1.0	−1.290	Moderate
Nov 2018	Dec 2018	1.0	−1.440	Moderate

Severity classifications based on Vicente-Serrano et al. [39]. Moderate: −1 to −1.5; Severe: −1.5 to −2; Extreme: < −2.

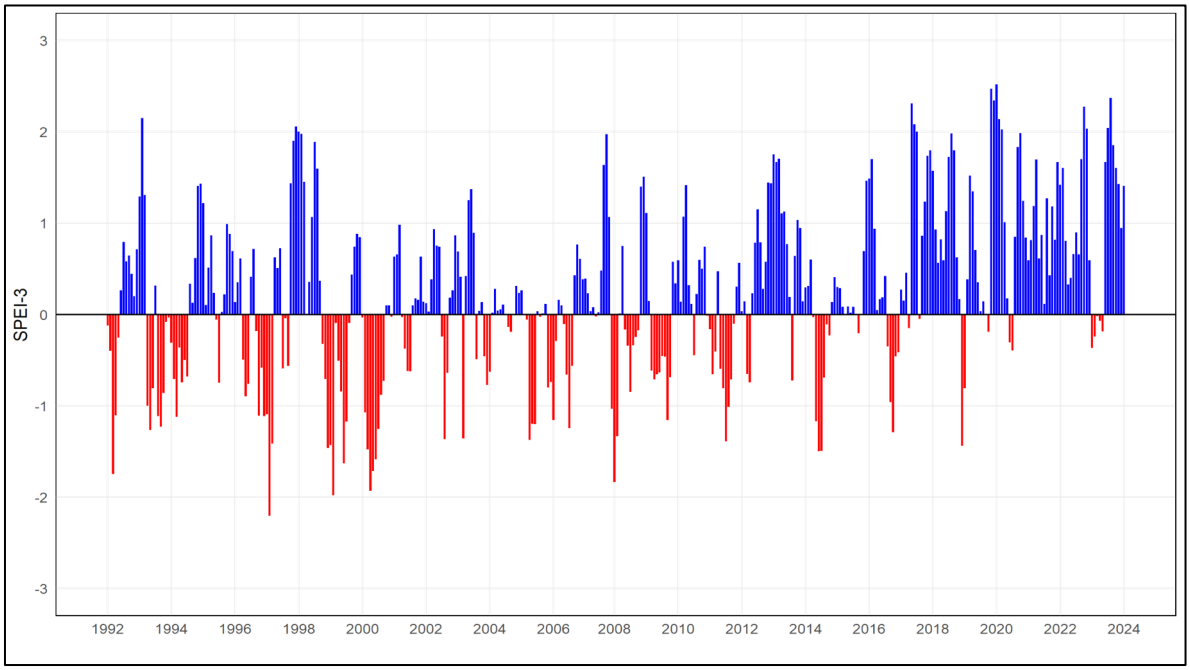

Figure 4. SPEI-3 for Kirisia Watershed from 1992 to 2023. Note: The Y-axis represents SPEI-3 value, the X-axis the Year and the horizontal lines at +1 and -1 indicate above-normal and drought thresholds respectively.

4.3. Meteorological Drought–Vegetation Productivity Relationship

Figure 5 presents the overlaid SPEI-3 and NDVI time series for Kirisia Watershed. Drought periods (negative SPEI-3) broadly correspond to suppressed NDVI values, while positive SPEI-3 periods align with higher NDVI.

Lag correlation analysis (Figure 6) identified the strongest Pearson correlation at a one-month lag ($r = 0.588$, $R^2 = 0.345$, $p < 0.001$), indicating that NDVI responds most strongly to SPEI-3 conditions from the preceding month.

SPEI-3 accounts for approximately 35% of NDVI variability over the study period. The remaining approximately 65% is attributable to factors including land cover change, grazing pressure, soil properties, and the drought-resistant character of the dominant woodland vegetation. This moderate correlation is consistent with findings in comparable woodland-dominated dryland systems [20] and contrasts with the strong correlations reported in cropland studies [8,44].

4.4. Pastoral Household Coping Strategies

4.4.1. Sociodemographic Profile

Table 2 presents the sociodemographic profile of the 70 survey respondents. Male household heads (75.71%) predominated, consistent with prior studies in the region [34]. This is reflective of Samburu cultural norms assigning resource governance authority to male heads [45]. The age distribution was concentrated in the 31–45 years group (47.14%), with 30% under 30 years. Education was heavily skewed towards lower attainment: 78.57%

had primary education or none. Household sizes were predominantly small (71.43% with five or fewer members), consistent with nomadic pastoral household structures in East African ASALs [29].

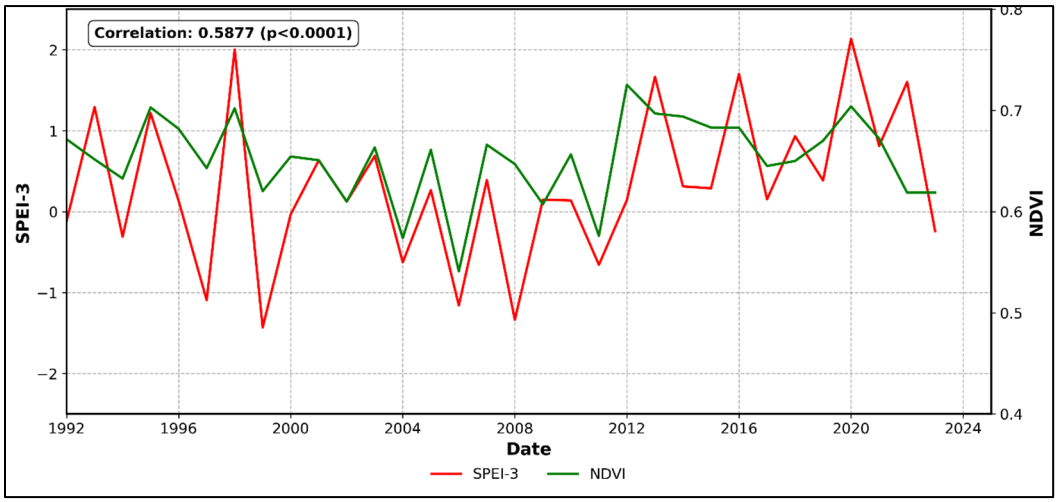

Figure 5. SPEI-3 and NDVI time series for Kirisia Watershed, 1992–2023.

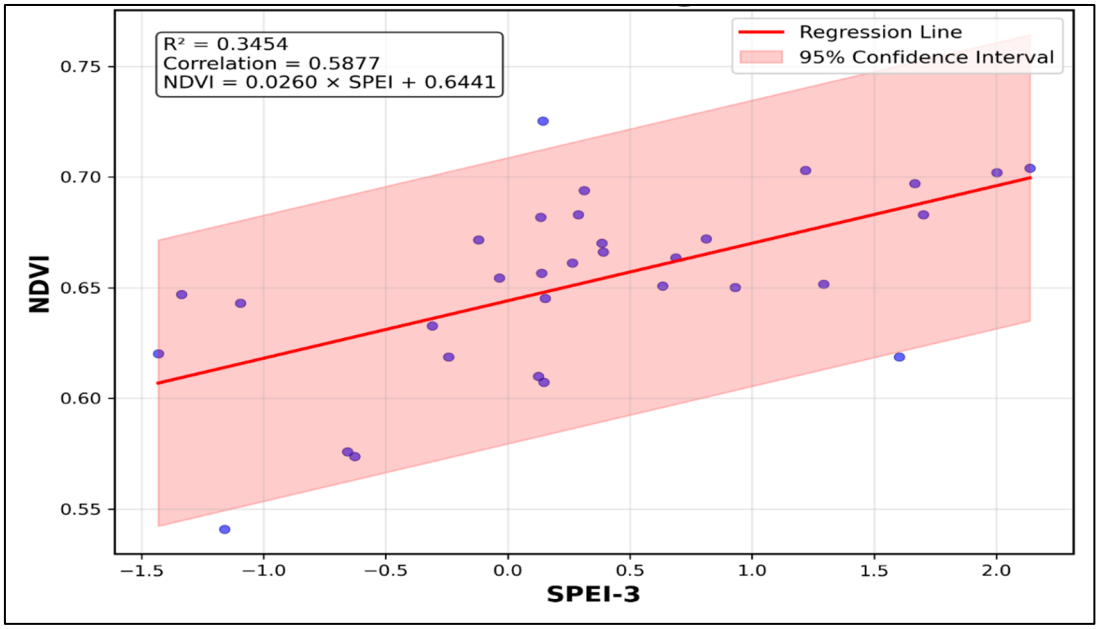

Figure 6. Pearson correlation between NDVI and SPEI-3 (one-month lag) for Kirisia Watershed, 1992–2023.

Table 2. Sociodemographic characteristics of survey respondents (n = 70).

Characteristic	Category	n	%
Sex of household head	Male	53	75.71
	Female	17	24.29
Gender of respondent	Male	46	65.71
	Female	24	34.29
Age (years)	18–24	11	15.71
	25–30	10	14.29
	31–45	33	47.14
	46–60	16	22.86
Education level	No formal education	27	38.57
	Primary	28	40.00
	Secondary	11	15.71
	Post-secondary	4	5.72
Household size	1–5 members	50	71.43
	6–10 members	13	18.57
	>10 members	7	10.00

4.4.2. Sociodemographic Associations with Coping Strategy Adoption

Table 3 presents the statistically significant associations between household sociodemographic characteristics and specific coping strategy significant under Monte Carlo testing ($p < 0.05$).

Table 3. Significant chi-square associations between sociodemographic characteristics and coping strategy adoption (n = 70; Monte Carlo $p < 0.05$ only).

Demographic Factor	Coping Strategy	χ^2 (df = 3)	Monte Carlo *p*
Education level	Migrated household	14.507	0.003
Respondent age	Migrated household	14.293	0.003
Education level	Engaged in business	9.286	0.032

Whole-household migration was associated with respondent education ($\chi^2 = 14.507$, $p = 0.003$) and age ($\chi^2 = 14.293$, $p = 0.003$). Migration was concentrated among households with no formal education (11 of 27, compared with 2 of 43 households with any formal education) and among respondents aged 46–60 years (8 of 16, compared with 5 of 54 respondents aged 45 years or younger). Younger respondents and those with formal education were therefore less likely to relocate the whole household. This may indicate that relocation is a necessity-driven response of households with fewer alternative livelihood options, although the cross-sectional design cannot test this.

Business engagement was associated with education level ($\chi^2 = 9.286$, $p = 0.032$). All seven households reporting it had some formal education (six primary, one post-secondary), and none of the 27 households with no formal education did. The pattern was not consistent across levels, because none of the 11 households with secondary education reported business engagement, and the small number of business households (n = 7) limits inference. As noted in Section 5.4, these tests were not adjusted for multiple comparisons and should be read as indicative rather than confirmatory.

4.4.3. Coping Strategies Employed

Figure 7 presents the distribution of primary coping strategies reported by the 70 surveyed households.

Relief assistance was the most frequently reported strategy (25.71%). This dependence on external support is striking given Samburu cultural norms around self-reliance and the social status tied to herd ownership [45]. Its prevalence suggests that successive droughts have progressively eroded the cultural and material resistance to external dependency. Relief assistance is inherently reactive and short-term as it addresses immediate survival but does not rebuild livestock assets nor restore long-term coping capacity.

Livestock migration was the second most common strategy (24.29%). However, the effectiveness of this strategy is increasingly constrained by land tenure change, and conservancy encroachment on traditional movement corridors [29]. Women are particularly affected as mobility withdraws the primary source of household milk at precisely the time of greatest stress [28].

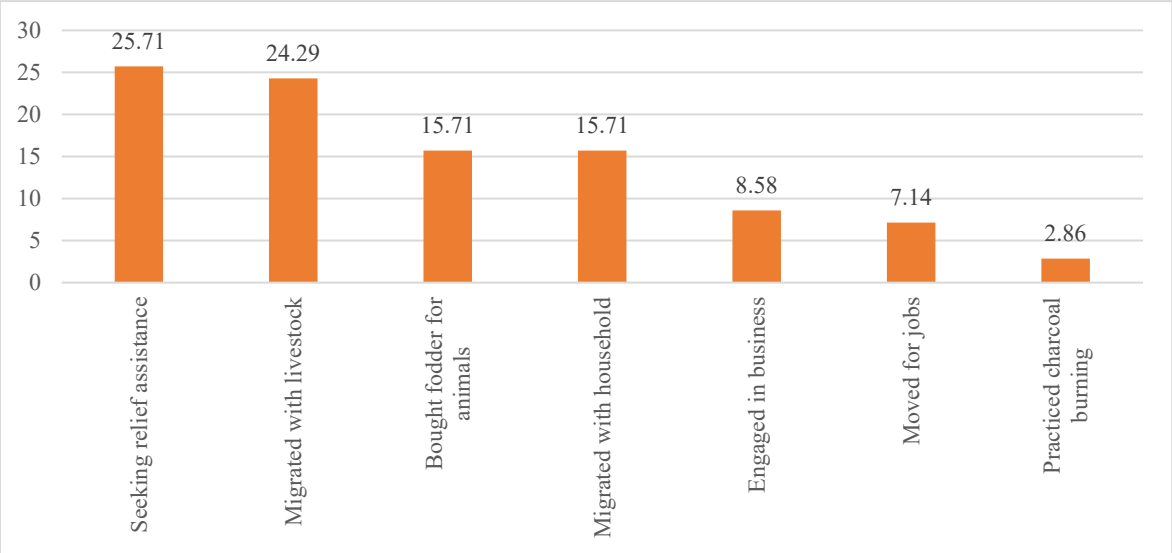

Figure 7. Primary coping strategies employed by pastoral households in Kirisia Watershed in response to meteorological drought.

These strategies are capital intensive. Business engagement (8.58%) and urban migration for employment (7.14%) were less common strategies. Charcoal burning, an ecologically destructive strategy and illegal strategy within the gazetted forest, was reported by only 2.86% of households.

4.4.4. Household Drought Perception

Open-ended responses on drought perception were coded into two broad themes: rainfall changes and drought changes. The dominant sub-theme was prolonged drought duration (30 mentions), far exceeding all others. Increased frequency (7 mentions) and shifting seasonality (7 mentions) were also prominent. Among rainfall-related perceptions, unpredictability was most frequently cited (6 mentions), followed by changes in rainfall intensity (4 mentions) and the failure of traditional prediction methods (3 mentions). The instrumental record shows a statistically significant trend towards increasing moisture over 32 years, yet households describe worsening drought duration and unpredictability. This finding is attributable to pastoral households experiencing variability and event-level duration, not long-term statistical means.

5. Discussion

5.1. The Wetter-Yet-More-Vulnerable Paradox

The central finding of this study is the coexistence of an increasing long-term SPEI-3 trend and worsening household reports of drought duration and unpredictability. This divergence should not be interpreted as evidence that the watershed has become objectively drier. Rather, it demonstrates that a positive trend in mean three-month moisture balance does not necessarily translate into lower drought impacts at the household level. Drought vulnerability is produced through interactions among climatic exposure, ecological sensitivity, and adaptive capacity; consequently, changes in any one component do not necessarily determine the direction of overall vulnerability [6,46].

The positive SPEI-3 trend reflects the long-term tendency in three-month moisture balance, particularly the transition from the drought-dominated 1999–2008 period toward generally wetter conditions after 2009. Pastoral households, however, experience drought through the timing, duration, sequence, and predictability of moisture deficits rather than through the long-term mean alone. The household responses in this study are therefore compatible with a wetter long-term mean if shorter or seasonally critical dry spells continue to disrupt forage availability and livestock condition. The perception results support this interpretation: prolonged drought duration was the most frequently reported drought change, followed by increased frequency and shifting seasonality. Drought occurrence and impacts can differ substantially according to the accumulation period used to characterise moisture deficits [6].

5.2. Vegetation Productivity Structural Decline and Ecological Buffering

The four high-confidence BEAST changepoints indicate that vegetation productivity in Kirisia Watershed has undergone meaningful structural change over the 31-year period. Their correspondence with drought events and ecological disturbances suggests that vegetation dynamics are shaped by the interaction of climatic variability and anthropogenic pressure rather than by drought alone.

The moderate SPEI-3–NDVI relationship ($R^2 = 0.345$) indicates that meteorological moisture conditions explain an important but limited share of watershed-scale vegetation variability. Vegetation response to drought is not determined by climatic stress alone; it is also shaped by vegetation structure, soil conditions, land-cover change, grazing pressure, and the capacity of ecosystems to buffer or recover from moisture deficits. The drought-resistant woodland vegetation dominant in Kirisia may therefore moderate the short-term response of NDVI to SPEI-3. Approximately 65% of NDVI variability remained unexplained by SPEI-3, reinforcing the need to avoid interpreting the correlation as a complete representation of ecological drought response. The relationship is also constrained by the spatial resolution of the AVHRR record and the use of a watershed-average series. Higher-resolution and multi-metric vegetation products could provide a more detailed assessment of ecological sensitivity in future studies.

5.3. Human Capital and Household Coping Capacity

Household coping capacity in Kirisia Watershed appears to be shaped by human capital. Education and respondent age were significantly associated with whole-household migration, and education with business engagement (Table 3). Migration was concentrated among older and uneducated households, suggesting that relocation is a necessity-driven response of households with few alternatives. Business engagement occurred only

among households with some formal education, consistent with education widening access to information, markets and non-pastoral income [47].

However, the predominance of low educational attainment among respondents suggests that many households remain constrained to reactive coping mechanisms. Similarly, education enhances coping flexibility by improving access to information, markets, and non-pastoral income opportunities [47]. However, the predominance of low educational attainment among respondents suggests that many households remain constrained to reactive coping mechanisms.

The dominance of relief assistance as the primary coping strategy indicates progressive erosion of household adaptive capacity. Reliance on relief support reflects not only immediate climatic stress but also declining access to sustainable coping alternatives. As such, relief dependence may itself serve as an indicator of vulnerability that should be monitored alongside ecological drought indicators.

5.4. Study Limitations

The household survey was cross-sectional and relied on a purposive, non-probability sample of 70 households. The sample therefore limits statistical power for detecting smaller effects and constrains generalisation beyond the sampled pastoral households in Kirisia Watershed. The coping-strategy associations were based on multiple pairwise tests across several sociodemographic variables and strategy categories; because no correction for multiple comparisons was applied, *p*-values should be interpreted cautiously and as indicative rather than confirmatory. Because expected cell counts were below 5 in several cross-tabulations, *p*-values were obtained by Monte Carlo permutation rather than the asymptotic chi-square approximation. Several groups were small (for example, seven households reported business engagement), which limits inference and precluded multivariable adjustment.

The AVHRR NDVI record has a spatial resolution of approximately 5.6 km, which is considerably coarser than the household and grazing-unit scales at which pastoral decisions occur. The moderate SPEI–NDVI relationship may therefore partly reflect scale mismatch. NDVI also has recognised limitations as a sole indicator of vegetation response: it can be influenced by soil background in sparsely vegetated environments, may saturate under denser vegetation, and measures greenness rather than plant-available water, biomass, or physiological stress directly. Future work should combine NDVI with complementary indicators such as vegetation condition or health indices, biomass observations, soil-moisture information, or microwave-derived vegetation metrics.

The cross-sectional household data were collected in a single year and therefore cannot establish whether the observed sociodemographic associations with coping are stable over time or causal. Drought perception data also relied on retrospective self-report and may be affected by recall and salience biases. The study further relies primarily on SPEI-3; drought characteristics at shorter and longer accumulation periods may differ, so the wetter-yet-more-vulnerable interpretation should be tested against multiple SPEI timescales in future work.

Finally, the study does not construct a formal composite vulnerability index. Instead, it examines separate indicators representing climatic exposure, ecological sensitivity, and adaptive-capacity proxies. The term "vulnerability" is therefore used in the conceptual IPCC sense, and the wetter-yet-more-vulnerable framing should be understood as an interpretation of divergence among these dimensions rather than as evidence of a statistically quantified increase in vulnerability.

6. Conclusions

Vegetation productivity in Kirisia Watershed has undergone substantial structural change over the past three decades. These changes appear to reflect interactions between climatic variability and non-climatic pressures. Although meteorological moisture conditions showed a statistically significant relationship with vegetation productivity, the moderate strength of the SPEI-3–NDVI relationship indicates that woodland characteristics and other environmental controls also influence vegetation dynamics.

The study identified a divergence between increasing long-term SPEI-3 moisture availability and worsening household reports of drought duration and unpredictability. This finding does not demonstrate that climatic exposure itself has increased. Rather, it shows that long-term mean moisture conditions alone are insufficient to characterise pastoral drought experience. Household vulnerability is shaped by the interaction of climatic exposure with ecological sensitivity and adaptive capacity, including the availability of viable coping options. The dominance of relief assistance and livestock migration, together with the observed associations between education, age, and selected coping strategies, points to socially differentiated coping capacity. These findings support drought-monitoring approaches that integrate climatic indicators with vegetation dynamics and household-level information at the watershed scale. Future studies should test the observed divergence using multiple drought timescales, higher-resolution vegetation products, spatially explicit analyses, and longitudinal household data.

Household coping capacity varied with education and age: whole-household migration was concentrated among older respondents and households with no formal education, and business engagement occurred only among households with some formal education. These associations are exploratory and require confirmation in larger samples.

These findings demonstrate the need for drought interventions that integrate ecological monitoring with socially differentiated resilience strategies at the watershed scale. Future research should prioritise multi-site comparative studies, longitudinal household monitoring, and investigation of additional ecological drivers such as land use change and soil properties that may influence vegetation productivity independently of meteorological drought.

Author Contributions

J.L.O.: Conceptualization, methodology, investigation, data curation, formal analysis, visualization, writing and original draft preparation. P.O.: Formal analysis, visualization, validation, writing and review. R.K.: Supervision, conceptualization, review and editing. All authors have read and agreed to the published version of the manuscript and agree to be accountable for their respective contributions and for ensuring that questions relating to the accuracy or integrity of the work are appropriately investigated and resolved.

Funding

This research received no external funding.

Institutional Review Board Statement

The study involved human participants and was conducted as part of the research requirements for an MSc in Integrated Watershed Management at Kenyatta University, Kenya. Research authorisation was obtained from the National Commission for Science, Technology and Innovation (NACOSTI) under permit number NACOSTI/P/23/24948. No additional separate IRB review was required for this study.

Informed Consent Statement

Informed consent was explicitly obtained from all participants before data collection. Participants were informed of the purpose of the study and the nature of their participation, and participation was voluntary.

Data Availability Statement

The satellite datasets used in this study are publicly available: NOAA AVHRR CDR NDVI Version 5 (https://www.ncei.noaa.gov); CHIRPS Version 3.0 (https://data.chc.ucsb.edu); CRU TS4.08 (https://catalogue.ceda.ac.uk). Household survey data are available from the corresponding author on reasonable request, subject to community consent protocols.

Acknowledgments

The authors thank the pastoral communities of Kirisia Watershed for their time, knowledge, and willingness to share data freely. We acknowledge the Kenya Forest Service, the National Drought Management Authority, and the community leaders and guides who facilitated fieldwork. We thank NOAA, UCSB-CHG (CHIRPS), and the CRU/CEDA for making long-term climate datasets publicly available. This study was conducted under NACOSTI Research Permit (NACOSTI/P/23/24948).

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

During the preparation of this work, the authors used ChatGPT (OpenAI) and Claude (Anthropic) to assist with language editing, improving clarity, paraphrasing, and refining the presentation of the manuscript. After using these tools, the authors reviewed and edited all AI-assisted content as necessary and take full responsibility for the accuracy, integrity, and content of the published article.

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